

VECTORIZACIÓN

Planteamiento

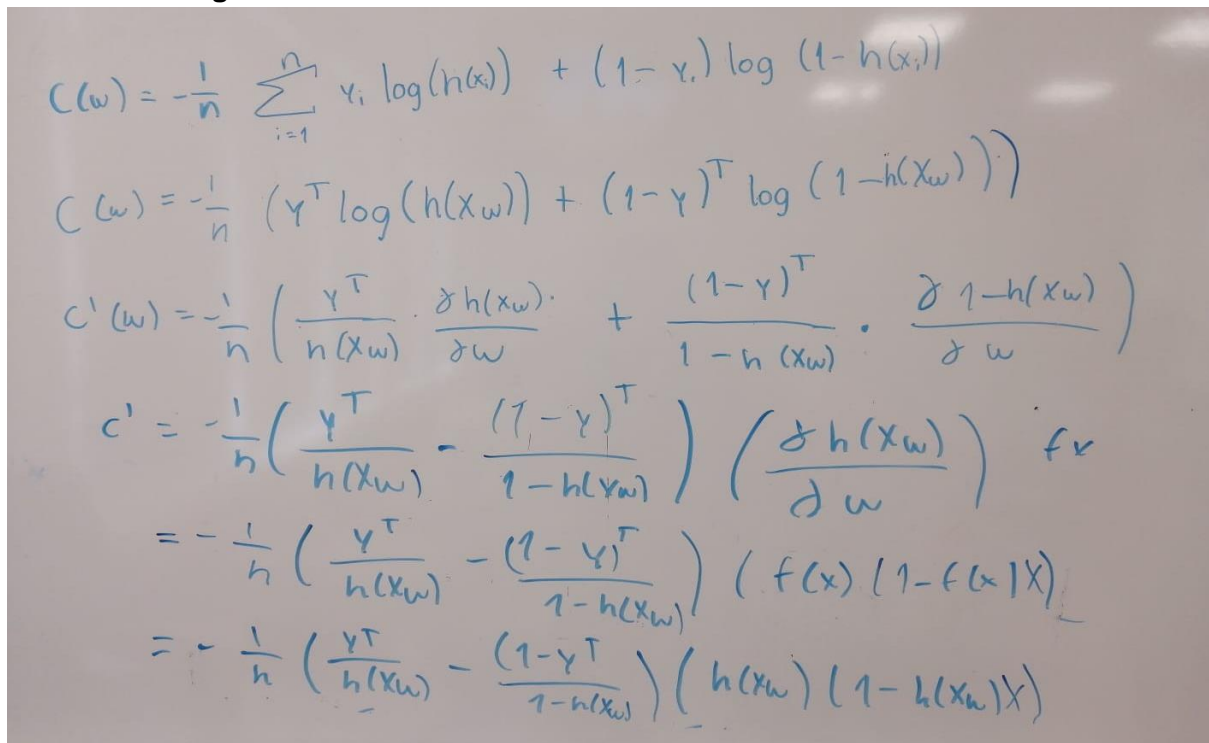
Regresión Logística

Sea $h(z) = p(z)$. Entonces, maximizar la función de máxima verosimilitud es equivalente a minimizar la siguiente función de costo:

$$\begin{aligned} C(w) &= -\frac{1}{n} \log(L(w)) = -\frac{1}{n} \sum_{i=1}^n y_i \log(h(x_i)) + (1 - y_i) \log(1 - h(x_i)) \\ &= -\frac{1}{n} (y^T \log(h(Xw)) + (1 - y)^T \log(1 - h(Xw))), \end{aligned}$$

donde $X \in \mathbb{R}^{n \times (k+1)}$, $w \in \mathbb{R}^{k+1}$ y $y \in \mathbb{R}^n$. Nótese que esta función de costo es convexa.


Obtención del gradiente de la función costo



Handwritten derivation of the gradient of the logistic cost function:

$$\begin{aligned} C(w) &= -\frac{1}{n} \sum_{i=1}^n y_i \log(h(x_i)) + (1 - y_i) \log(1 - h(x_i)) \\ C(w) &= -\frac{1}{n} (y^T \log(h(Xw)) + (1 - y)^T \log(1 - h(Xw))) \\ C'(w) &= -\frac{1}{n} \left(\frac{y^T}{h(Xw)} \cdot \frac{\partial h(Xw)}{\partial w} + \frac{(1 - y)^T}{1 - h(Xw)} \cdot \frac{\partial (1 - h(Xw))}{\partial w} \right) \\ C' &= -\frac{1}{n} \left(\frac{y^T}{h(Xw)} - \frac{(1 - y)^T}{1 - h(Xw)} \right) \left(\frac{\partial h(Xw)}{\partial w} \right) \quad \text{fr} \\ &= -\frac{1}{n} \left(\frac{y^T}{h(Xw)} - \frac{(1 - y)^T}{1 - h(Xw)} \right) (f(x) (1 - f(x)) X) \\ &= -\frac{1}{n} \left(\frac{y^T}{h(Xw)} - \frac{(1 - y)^T}{1 - h(Xw)} \right) (h(Xw) (1 - h(Xw)) X) \end{aligned}$$

$$\begin{aligned}
 &= -\frac{1}{n} \left[\frac{y^T h(x_w) (1-h(x_w)) X}{h(x_w)} - \left(\frac{(1-y)^T h(x_w) (1-h(x_w)) X}{1-h(x_w)} \right) \right] \\
 &= -\frac{1}{n} [y^T (1-h(x_w)) X - (1-y)^T h(x_w) X] \\
 &= -\frac{1}{n} y^T X - \cancel{y^T h(x_w) X} - (h(x_w) X + \cancel{y^T h(x_w) X}) \\
 &= -\frac{1}{n} y^T X - h(x_w) X \\
 &= -\frac{1}{n} X (y^T - h(x_w)) \\
 &= \frac{1}{n} X (h(x_w) - y^T)
 \end{aligned}$$

 ADIÓS?

Demostración de igualdad entre las dos funciones

eq1 = eq2

$$\begin{aligned}
 \text{eq2} &= C(w) = -\frac{1}{n} (y^T \log(h(x_w)) + (1-y)^T \log(1-h(x_w))) \\
 \text{eq1} &= C(w) = -\frac{1}{n} \sum_{i=1}^n y_i \log(h(x_i)) + (1-y_i) \log(1-h(x_i))
 \end{aligned}$$

dotProduct == Suma ponderada
 $a^T \cdot b = \sum_i a_i b_i$
 Edge Cases
 $y=0 \rightarrow$ lo afecta pq al tener dotProduct de 0
 $y=1 \rightarrow$ no afecta porque $(1-y)$

$x_i = w \cdot X$
 $h(x_i) = w \cdot x_i$
 $h(x_i) = h(wX)$

$a_i = y_i$
 $b_i = \log(h(x_i))$
 $a_i = 1-y_i$
 $b_i = \log(1-h(x_i))$

Constante Suma ponderada 1 Suma ponderada 2

$$\begin{aligned}
 &(y^T) \cdot \log(h(wX)) + (1-y)^T (\log(1-h(x_w))) \\
 &= -\frac{1}{n} (\text{Suma ponderada 1} + \text{Suma ponderada 2})
 \end{aligned}$$